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# An IoT-based Deep Learning Approach to Analyse Indoor Thermal Comfort of Disabled People

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## Abstract

Monitoring the thermal comfort of building occupants is crucial for ensuring sustainable and efficient energy consumption in residential buildings. Existing studies have addressed the monitoring of thermal comfort through questionnaires and activities involving occupants. However, few studies have considered disabled people in the monitoring of thermal comfort, despite the potential for impairments to present thermal requirements that are significantly different from those of an occupant without a disability. Additionally, people with disabilities can experience difficulties in expressing their thermal comfort, which further complicates assessment and monitoring. To overcome this, we propose the development of a new learning model using a deep neural network. Our model can predict the indoor thermal comfort of differently abled people in real time to facilitate remote monitoring. We generated our real dataset using a new Internet of Things (IoT) architecture. Our architecture also includes a data collection scheme to ensure an efficient collection process, enabling the collection of targeted data before transferring them to cloud servers for further data analysis. Experimental results illustrate the reliability of our data collection scheme in gathering useful and targeted data, as well as the efficiency of our deep learning-based model, which achieved an accuracy of 94% and a precision and recall of 98% and 97%, respectively.

*Keywords:* Building sustainability, Disabled people, Indoor thermal comfort prediction and monitoring, Deep learning, Internet of Things (IoT).

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## 1. Introduction

People spend approximately 90% of their time indoors, and almost 70% of that time is spent at home [1]. In addition, there were an estimated 50,100 excess winter deaths during the 2017 to 2018 winter season, according to the Office of National Statistics of the United Kingdom [2]. Thus, well-being is strongly affected by indoor comfort. Therefore, real-time assessment of thermal comfort is essential for improving indoor climates for building occupants.

Recently, monitoring indoor thermal comfort has emerged as a promising solution for building sustainability by improving both the comfort of occupants and the energy consumption of buildings [3] [4] [5]. In this context, several models have been designed for measuring indoor thermal comfort [6][7]. For instance, predicted mean vote (PMV) and predicted percentage dissatisfied (PPD) models have been proposed by Fanger [6]. PMV and PPD have become the basis of many standards, including ISO 7730 and ASHRAE 55 [8][9]. The PMV estimates the indoor thermal comfort of a group of people on a seven-point thermal sensation scale (see Table 1).

Table 1: The seven point of Thermal Sensation.

-3	Cold
-2	Cool
-1	Slightly cool
0	Neutral
+1	Slightly warm
+2	Warm
+3	Hot

The PMV index is based on six main parameters in two categories. Human activity and clothing insulation are categorized as the two human parameters, whereas air relative humidity, air temperature, mean radiant temperature, and air velocity are categorized as the four environmental parameters. On the other hand, PPD measures the percentage of thermally dissatisfied people who feel too cool or warm (Figure. 1). However, PMV is based on a very complex mathematical expression because it depends on both human and environmental parameters, which makes it difficult to measure. Hence,

building a prediction model of PMV values is necessary for enabling real-time PMV monitoring. In this context, several studies have addressed PMV value prediction using traditional machine learning algorithms, such as classification trees, logistic regression, and the Naive Bayes classifier [10][11][12].

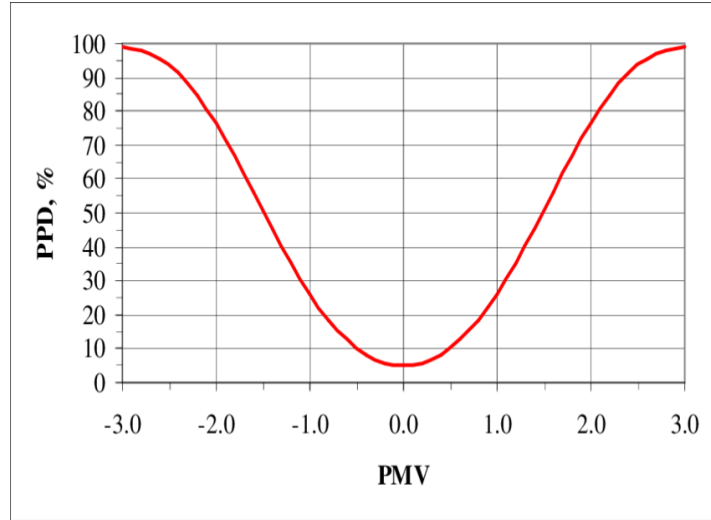


Figure 1: Thermally dissatisfied occupants (PPD) based on PMV values.

Furthermore, another class of studies has addressed the thermal comfort monitoring of people who are either sleeping [13][14][15] or engaged in an activity [16][17][18]. However, few studies have addressed the thermal comfort of disabled people [19][20][21]. Parsons and Webb [20] studied feedback provided by 16 disabled people (eight females and eight males) in a living room over a 3h period. A significant variation in response sensations was noticed, especially between slightly cool, cool, and neutral sensations. Moreover, the same authors studied the requirements of 32 people with different sclerosis [21]. These people were exposed to three conditions: 29°C (slightly warm to warm); 23°C (neutral); and 18.5°C (slightly cool to cool). They noticed that these specific populations had a wide range of responses under the three experimental conditions. In addition, the measured percentage of dissatisfied people was much higher than that predicted by Fanger’s PPD. Therefore, disabled people have specific requirements which are different from those of people without disabilities. This is mainly because of anthropometric and postural differences as well as mobility. Moreover, the disability itself

may also affect thermoregulatory responses such as sweating, shivering, and changes in blood flow. Therefore, the thermal comfort requirements for disabled people must be studied specifically.

In [22], we proposed a new framework to deploy sensors and collect data related to people’s thermal comfort. In this study, we extend our previous work by collecting a real dataset over a period of six months, which is required to determine the PMV index. Our data are related to the thermal comfort of disabled people and were collected from a residential building (A.P.E.I<sup>1</sup>). The dataset was then used to train a thermal comfort classifier using a deep learning algorithm called the ‘*artificial neural classifier (ANC)*’. Deep learning is emerging as an advanced machine-learning algorithm which outperforms traditional machine learning schemes [23][24]. Deep learning is based on a neural network which consists of three layers: input, hidden, and output. The input layer contains the inputs, the hidden layer processes the inputs, and the output layer produces the result. Essentially, each layer attempts to learn certain weights. Typically, machine learning neural networks comprise 1 or 2 hidden layers [25], whereas deep learning networks can have up to 150 hidden layers. Hence, deep learning can efficiently model complex non-linear relationships between data, including related thermal comfort data. Thus, we chose to implement a deep ANC network to model thermal comfort prediction. To the best of our knowledge, our work is the first to use the deep learning concept to deal with the thermal comfort of disabled people using a corresponding real dataset. Thus, our trained classifier can be utilized to predict PMV values online. Furthermore, the predicted comfort can be exploited by building managers to make suitable decisions in order to improve indoor thermal comfort, such as opening doors and windows for ventilation, changing occupants’ clothing, and turning on/off air conditioner (AC). Therefore, our prediction model can help to efficiently manage HVAC systems according to the predicted comfort of disabled people. We have previously conducted another study [26] on predicting indoor thermal comfort using the multiple linear regression (MLR) algorithm [27]. However, such previous work focuses on people without physical disabilities and is based on a publicly available dataset and a traditional machine learning algorithm.

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<sup>1</sup>A.P.E.I is an association of parents of people with physical disabilities, in Troyes city, situated in east of France.

The main contributions of this study are as follows.

- A new IoT architecture is designed to enable remote access to information regarding the thermal comfort of disabled people.
- We provide an optimisation scheme which is implemented alongside the IoT-based architecture to improve the reliability and efficiency of the data collection process [22].
- We collected a dataset containing the thermal comfort information of the disabled residents of a residential building, recorded over six months. We focused on information related to the PMV index measurement, such as temperature, humidity, clothing level, and metabolic rate.
- Using our collected data, we built a prediction model of thermal comfort for differently abled people using a deep learning algorithm. Our classifier model can predict PMV values remotely. Hence, it helps in making adequate decisions when detecting a lack of indoor thermal comfort.

The rest of this article is organized as follows. Related work is introduced in Section 2. Section 3 details our proposed schemes for collecting, predicting, and monitoring occupants' thermal comfort. We discuss experimental results obtained through the simulation in section 4. Finally, we conclude the paper in Section 5.

## 2. Related Work

Several studies have been conducted on indoor thermal comfort. These studies have focused on measuring indoor thermal comfort based on data collected to monitor and control the thermal comfort of occupants [16][17][15][28]. We classify these studies into two categories: (i) those aimed at people with physical disabilities [29][30][31] and (ii) those aimed at people without physical disabilities who are either sleeping [13][14][15] or awake [16][17][18].

### 2.1. Thermal Comfort of Disabled People

*Jan et al.* [29] analysed patients' thermal comfort by considering subjective measurements via questionnaires and objective measurements, such as personal and environmental measurements. They focused on 99 patients from different wards, including oncology, maternity, neurology, and abdominal surgery. In this study, both PPD and PMV indices were derived from ISO 7730 [8]. The authors deduced that no significant difference between PMV and actual mean vote (AMV) was obtained from either measurement or for targeted wards except neurology. Similarly, a literature review on the thermal comfort of hospital occupants, including patients and hospital personnel, was proposed by *Jamal et al.* in [30]. They deduced that it is important to initiate new studies addressing the relationship between the productivity of hospital staff and indoor thermal comfort conditions.

A questionnaire was used by *Hill et al.* to review the experience of 38 caregivers about the thermal requirements of disabled people [31]. The questionnaire focused on issues related to specific disabilities, environmental conditions, and human responses. A total of 76% of the response suggest that disabled people have different thermal comfort needs.

### 2.2. Thermal Comfort of Awake People

To save energy in buildings in Singapore, *Chaudhuri et al.* [16] studied the occupants' thermal comfort by predicting the individual thermal comfort level of 817 occupants in an air-conditioned building. The aforementioned study was conducted using a publicly available database comprising several parameters, such as Fanger's six parameters, age, gender, and outdoor temperature. To predict the thermal comfort of occupants, the authors used six machine learning algorithms. Prediction accuracies between 73% and 81% were achieved using the proposed approach.

*Farhan et al.* [17] introduced a new SVM classifier-based approach to predict human thermal comfort and suggested corresponding actions to improve overall thermal comfort, especially for senior citizens. The learned classifier takes a vector of features as input, including Fanger's features, outdoor temperature, and age, outputs the corresponding thermal sensation level ("neutral", "feeling warm", and "feeling cold"), and achieves a prediction accuracy of up to 76.7%. Similarly, another SVM classifier has been implemented to predict human thermal comfort [32]. Different information was used, while also including Fanger's features. The results show an acceptable correlation

between the predicted values and those obtained through existing models, such as the “2-Node” model and the Fanger Model [33].

*Nian and Wang* [18] aimed to ensure comfortable indoor thermal environment while reducing energy consumption. As input parameters, the authors used two new parameters in addition to Fanger’s six parameters—the number of people in the room and the indoor CO<sub>2</sub> concentration. They then used a back propagation (BP) neural network algorithm to predict the PMV value.

*Hu et al.* [34] introduced a thermal comfort management system (iTCM) based on a sensor network to collect data related to thermal comfort. Then, they implemented a neural network to predict thermal comfort. The obtained results show that this model outperforms the PMV model by up to 17.8%, with an average of 13.1%.

*Irshad et al.* [35] studied the real behaviour of occupants inside a test room equipped with a thermoelectric air duct (TE-AD) cooling system. They first collected real data from this room for two months. Subsequently, they implemented three artificial neural network (ANN) models to predict the occupants’ thermal comfort, taking the following parameters: air and globe temperatures, relative humidity, clothing value, metabolic rate, and wind speed. The obtained results show that the first model is more accurate in predicting the PMV value, while M3 provides the best accuracy in predicting the PPD value.

*Javed and al.* [36] developed an Android application that enables occupants to communicate their thermal comfort sensation. The collected data are then used to train the thermal comfort model using the support vector classification (SVC) algorithm. The accuracy of the SVC algorithm (95.80%) was compared with that of other algorithms, such as KNN (90.40%) and decision tree (85.80%).

### 2.3. Thermal Comfort of Sleeping People

A theoretical study on indoor thermal comfort of occupants sleeping in buildings, bedrooms, residences, or hotels was conducted by *Lin and Deng* [13]. The authors derived a comfort equation that suits the sleeping thermal environment by modifying Fanger’s model. To solve the equation, the authors defined comfort charts which can also be used to determine thermally neutral conditions in a bedding system.

*Pan and al.* [14] aimed to determine gender differences in sleep comfort. The authors used various temperatures from 17 °C to between 20 °C and



23 °C and measured the finger and mean skin temperatures in addition to finger blood flow, through questionnaires. They deduced that men prefer a lower indoor temperature during sleep than women. In addition, both finger skin temperature and finger blood flow were lower for females than for males, while the mean skin temperature of males was lower than that of females.

*Shen et al.* [15] studied the impact of both cyclic position change during sleep and mattress design on sleep thermal comfort, and hence on sleep quality. They deduced the relationship between variables related to appraisal and mattress design. Similarly, *Tan et al.* in [28] observed variations in sleeping posture in order to design a comfortable mattress according to body position distributions. Ten people participated in the sleep control experiment, which was conducted to observe all features impacting sleeping postures. Moreover, the subjective feelings of the participants were analysed via a questionnaire to designed the mattress suitably.

#### 2.4. Discussion

Table 2 compares the above-mentioned studies according to many criteria: the state of people (awake or sleeping people), the algorithm and parameters used to study the indoor thermal comfort, prediction accuracy for works that are based on a machine learning algorithm to predict thermal comfort, and the population based on each study. We notice that most of the above works address awake people without physical disabilities. They studied the indoor thermal comfort through either machine learning algorithms to measure and predict the thermal comfort of awake occupants, or theoretical studies to assess both the thermal comfort during sleeping states and the sleeping quality under different conditions. We also observe that most of the studies are based on Fanger’s parameters, in addition to other variables, such as age, gender, and outdoor temperature. It is worth noting that studies focused on disabled people are limited to reviews of thermal comfort requirements. These studies have concluded that special attention should be paid to people with disabilities, especially under uncomfortable conditions. Therefore, to the best of our knowledge, no work has addressed the thermal comfort prediction of disabled people. These conclusions bring us to generate a prediction model that leverages the recent deep learning concept, and hence provides real-time monitoring of indoor thermal comfort. Moreover, our prediction model is based on real data related to disabled people which were also generated for our study.

Table 2: Comparative study between indoor thermal comfort works.

	People state		Used algorithm	Used parameters	Prediction accuracy	Disabilities	
	Awake people	Sleeping people				With	Without
Chaudhuri et al. [16]	X		SVM, ANN, LR, LDA, KNN, CT	Fanger's parameters, age and gender	Between 73% and 81%		X
Farhan et al. [17]	X		SVM	Fanger's parameters	76, 7%		X
Nian and Wang [18]	X		Neural network	Fanger's parameters, people in room	—		X
Javed and al. [36]	X		SVC	Fanger's parameters	95, 8%		X
Lin and Deng [13]		X	Theoretical study	Fanger's parameters	—		X
Pan al. [14]		X	Online survey study	Indoor temperature, skin temperature, blood flow.	—		X
Shen et al. [15]		X	Theoretical study	Cycle position change, mattress design	—		X
Tan et al. [28]		X	Theoretical study	Changes of sleeping posture	—	9	X
Jan et al. [29]	X		Theoretical study	Fanger's parameters	—	X	X
Jamal et al. [30]	X	X	Literature review	Fanger's parameters	—	X	
Hill et al. [31]	X		Theoretical study	Fanger's parameters	—	X	
Hu et al. [34]	X		ANN	Fanger's parameters	—		X
Megri et al. [32]	X		SVM	Fanger's parameters	—		X
Irshad et al. [35]	X		ANN	Fanger's parameters	—		X

### 3. Thermal Comfort Prediction of People with Physical Disabilities: An IoT-Based Architecture

In this section, we present our Deep learning based scheme for remote thermal comfort measurement. Subsection 3.1 provides an overview of our Internet of Things (IoT) architecture. The adopted data collection process is introduced in subsection 3.2, and finally we present our real dataset and deep learning algorithm to measure and predict the indoor thermal comfort in subsection 3.3.

#### 3.1. Remote Availability: Providing targeted data remotely and in real-time

Our thermal comfort prediction process involves three main steps: (i) data collection from A.P.E.I. buildings; (ii) data transfer to a remote cloud; and (iii) data storage and processing using a deep learning algorithm for effective decision-making.

Thus, we first used a set of sensors in the A.P.E.I. building to record thermal comfort data. These data were then transferred to the remote cloud through gateways and routers for further processing. Figure 2 shows our designed 3-layer architecture, which comprises the following:

1. **Perception layer:** We utilized three different types of sensors to collect information related to indoor humidity, temperature, and air velocity. As in several studies [37], we assumed that the air temperature is equal to the mean radiant temperature, because the latter is difficult to measure and requires multiple sensors. In addition, the clothing insulation and metabolic rate of disabled people were recorded through daily online surveys. Moreover, we used HD32:3 ice WBGT equipment, which enables measurement of both the PMV and PPD [38].
2. **Network layer:** Data is routed from the perception layer to the cloud layer through the gateway and router devices. In [39], we proposed a scheme that adjust the data throughput of sensors when sending their data. In addition, in our practical experiment, Wi-Fi was used as the radio access technology (RAT).
3. **Cloud layer:** This is the most important layer, as it is in charge of aggregating, storing, and processing received data. The feedback of this layer will then help end users in A.P.E.I. buildings to make adequate decisions toward improving the indoor thermal comfort. Thus, this

layer provides a set of network services to end-users, including real-time monitoring, statistical analytics, and graphical visualisation.

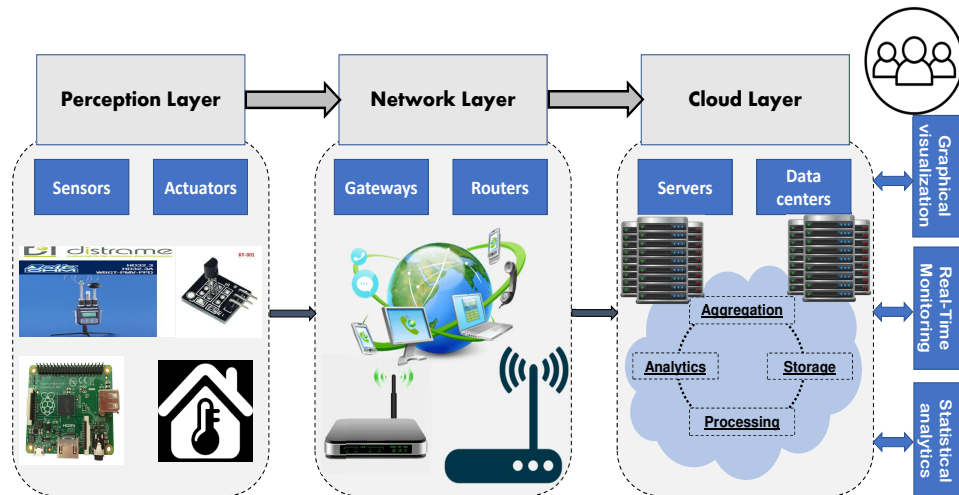


Figure 2: Our 3-layers Internet of Things architecture.

### 3.2. Collection Process: how to collect indoor thermal comfort variables?

The proposed architecture incorporates two main schemes. The first involves sensor installation in the building, while the second addresses the data collection challenge. In fact, sensor nodes are placed in the building in such a manner that all rooms are covered. The sensors are maintained periodically (once per month) by people working in the building.

In our architecture, sensor nodes periodically transfer sensed data, such as humidity, indoor temperature, and air velocity, to the remote cloud data centres for further processing (Figure. 3-(A)). However, some issues must be addressed during data collection. For example, redundant data may be collected by the same sensor, such as similar air quality or temperature readings, which would result in redundant information being transferred to the cloud data centres. This would in turn lead to a higher probability of network congestion and technical problems. In this context, the transferred information (data packets) can be aggregated to minimise network overhead while ensuring high data accuracy. Data aggregation aims to delete data redundancy and hence reduce the number of data packets delivered to the cloud. The idea is to measure the similarity between sensed sample data using existing

techniques, including Mahalanobis and Euclidean distances [40].

In this study, we are based on the same data collection scheme that we proposed in [22]. The basic idea of our data collection scheme is to measure the dissimilarity degree between the gathered data as a data quality metric by applying the average Euclidean distance technique. More specifically, the cloud data centre calculates the degree of dissimilarity between the received data from the same sensor. It then sets the sleeping time interval of the sensor accordingly (Figure. 3-(A) and (B)). In other words, the higher the data quality, the more frequently the data are sent from sensors to the cloud server, and vice versa.

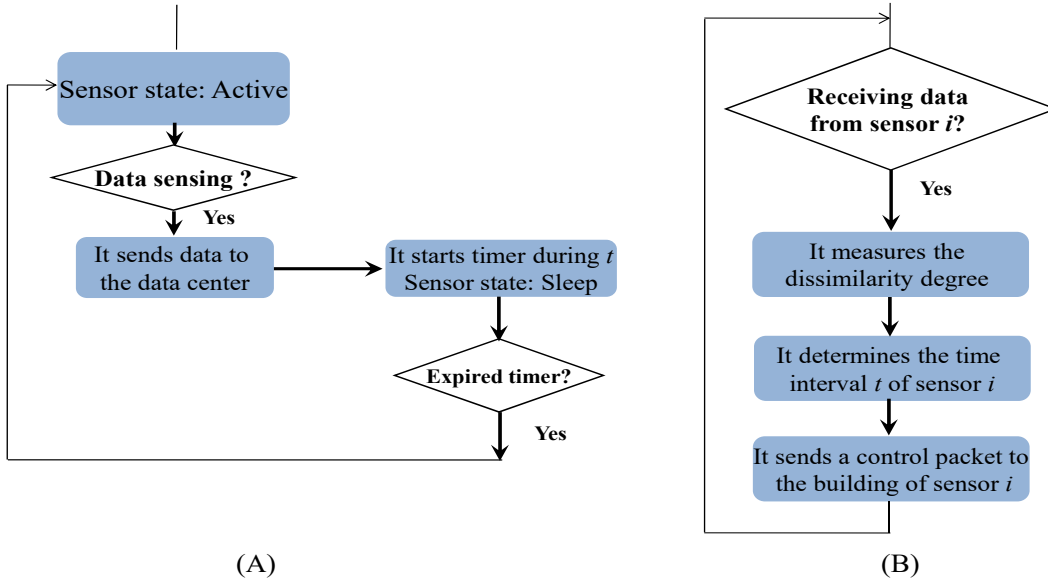


Figure 3: The data collection process: (A) by a sensor  $i$ , (B) by the remote data center.

### 3.3. Thermal Comfort Prediction: how to measure the indoor thermal comfort?

In this section, we present our prediction model that we create using deep neural network and our real dataset related to disabled people.

### 3.3.1. Our Deep Learning Model

We use artificial neural networks (ANNs) to build our prediction model, which is based on a multi-layer perceptron (MLP) model. MLP is a class of multi-layer feed-forward ANNs and is composed of at least three layers of neurons: input layer, hidden layer, and output layer [41].

In our study, we used supervised deep learning. With supervised learning, a training dataset was fed to the neural network as input. Each input observation was labeled with an output value. Thus, a neural network learns the output corresponding to each input. For example, we consider our dataset observations, which can be classified into seven different PMV categories. Thus, we have a sequence of pairs,  $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ , as the training set. Where  $x_i$  is the input observations and  $y_i$  is the PMV class output. The training is performed in such a manner that the cost function is minimized. The latter represents the distance between the predicted and real PMV classes.

Moreover, supervised learning can be further categorized as classification or regression learning based on the output variable values. The output variable is numerical for regression and categorical for classification. In our case, because  $y_i$  is categorical data (seven classes of PMV), we used supervised classification learning. We implemented an artificial neural classifier (ANC) to build a prediction model for PMV classes.

### 3.3.2. Offline thermal comfort prediction

Our ANC algorithm aims to learn a function that represents the relationship between both input features in terms of thermal comfort conditions and the output thermal sensation scales (PMV classes). This training step was performed offline, as illustrated in Figure. 4. We also focus on three types of disability: physical, learning, intellectual, and neurological disabilities.

1. Longitudinal Data Collection Step: Our study is based on longitudinal data of 10 occupants, 3 females and 7 males, between 18 and 25 years of age. Our data were collected over six months, from July to December 2017, at the A.P.E.I. building in Troyes city, France. We note that Troyes city is characterised by intense cold or excessive heat, representing a “humid oceanic temperate” climate. Troyes is 112 m above sea level and is a city with high rainfall ( average annual rainfall of 827 mm). Troyes has an average annual temperature of 11.5°C.

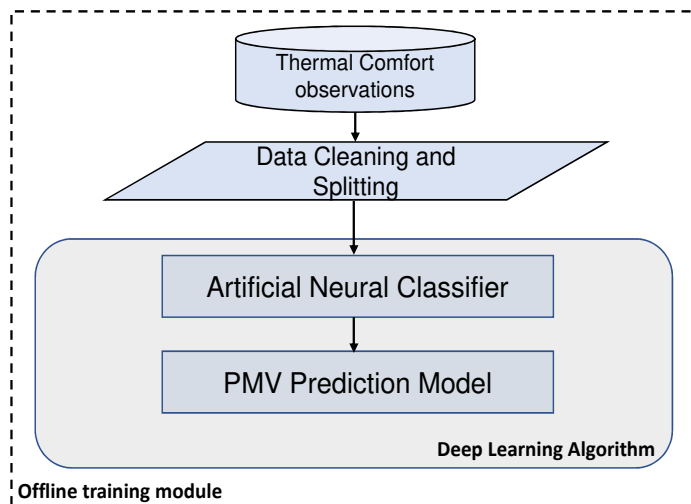


Figure 4: Our Offline training module.

Among these 10 occupants, 3 persons have a physical disability, 3 persons have a learning disability, and 4 persons have a neurological disability. These data were collected every 15 min through both sensor measurements and online daily surveys of indoor thermal comfort. Table 3 describes our dataset in terms of location study, time frame, and different features. It comprises eight features ( $f = 8$ ) as input data: the six Fanger’s features, absolute time, disability type, thermal sensation of occupants, and PMV values as output data. The total number of observations was  $d = 10 \times 96 \times 180 = 172800$  observations.

Besides, we have measured the indoor PMV value in two different ways: (i) We used HD32.3 WBGT hardware, which is a data logger for WBGT, PMV, and PPD measurements [42]; (ii) we designed a new tool in the form of a vertical ruler (plastic, A5 format) to perform daily surveys. This tool represents a thermometer ranging from very cold to very hot. Five drawings of a more or less dressed man are associated with the different temperatures (Figure 5). Thus, the task of people with disabilities is to indicate (orally or by pointing to an image corresponding to their opinion) how they feel in terms of heat/cold. This tool is easy to use by people with physical disabilities and depends only on their ability to communicate (orally or by pointing); hence, it does not pose major concerns for these people. In addition, Raspberry Pi-based sensors were used to measure the indoor environmental parameters,

Table 3: Description of our collected dataset.

Location study	Troyes (France)			
Time Frame	July 2017– December 2017			
DATASET COLUMN	CATEGORY	NAME	SOURCE	UNITS
1	GENERAL	Time	—	Absolute Time
2	PERSONNEL	Disability Type	—	String
3	ENVIRONMENT	INDOOR Ambient Temperature	Temperature Sensor	°C
4	ENVIRONMENT	INDOOR Relative Humidity	Humidity Sensor	%
5	ENVIRONMENT	INDOOR Air Velocity	Air Velocity Sensor	m/s
6	ENVIRONMENT	INDOOR Mean Radiant Temp	Temperature Sensor	°C
7	PERSONNEL	Metabolic Rate (last 30 min))	Daily Surveys	MET
8	PERSONNEL	Clothing Level	Daily Surveys	CLO
9	MODEL	Predicted Mean Vote (PMV)	HD32:3 WBGT + Daily Surveys	Limited to [-3, 3]

including temperature, humidity, and air velocity. The Raspberry Pi used has a 700 MHz ARM11 processor. It includes 1, 2, or 4 USB ports, an *RJ45* port, and 256 MB of RAM for the original model (1 GB on the latest versions). Furthermore, both metabolic and clothing levels are set by the persons who manage the building based on tasks performed by disabled people as well as their clothing, respectively.

2. Data Cleaning and Splitting Step: Improving the quality of data directly improves the accuracy of the learning model, as the latter learns from them. Thus, this step consists of eliminating duplicated data and normalising them in terms of format and scale. We used the Min/Max scaling method to place the data values in the same range and scale (between 0 and 1). In addition, these data must be divided into two parts: training and testing sub-sets, for training and validation of the



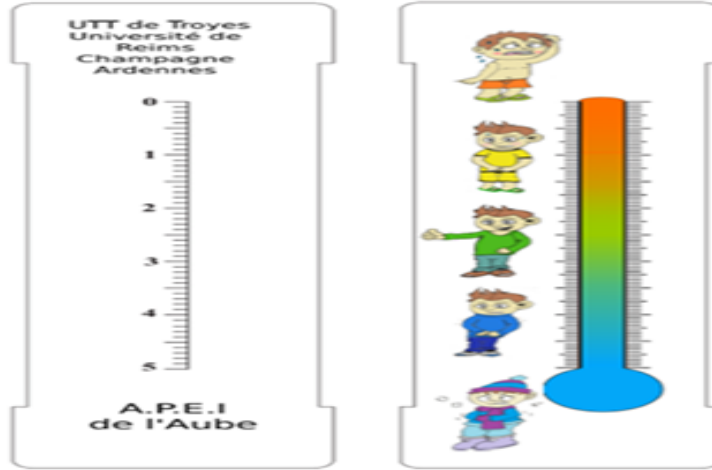


Figure 5: Our Vertical Ruler for Thermal Feeling Measurement.

prediction model, respectively. In our case, we used 75% of the data for model training, while 25% of the data were used for the validation/test step.

3. Supervised Learning Classifier: We utilize an artificial neural classifier algorithm (ANC) to build the prediction model for seven scales of the PMV. Our ANC comprises mainly (Figure 6): (i) input layer of eight neurons that correspond to our eight input features; (ii) three hidden layers of six neurons each that map the inputs to an output; and (iii) an output layer corresponding to the predicted PMV value. Bias-corrected input data values are passed through the ReLU activation function to obtain an output [23]. We note that we have implemented many configurations regarding the number of hidden layers and neurons in each layer. We then chose the configuration that gave us the best performance in terms of prediction accuracy while reducing the time complexity.

To build the prediction model, the training set is passed several times (training epochs) to the hidden layers of the neural network. For improving accuracy, the parameters of the neural layers are updated at each epoch using the stochastic gradient descent (SGD) algorithm [43].

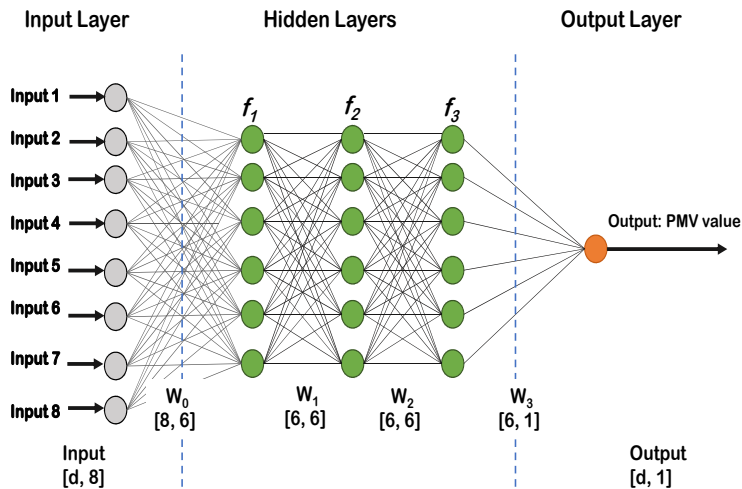


Figure 6: Implemented Neural Network Architecture.

## 4. Performance Evaluation

This section presents an experimental study to validate our data collection and thermal comfort prediction schemes.

### 4.1. Simulation Setup and Parameters

To validate our data collection scheme, we focused on one A.P.E.I. building, while varying data collection parameters, such as the number of covered rooms and the number of times the sensors send their data to the cloud (iterations).

We aim to validate the performance of our scheme at: 1) avoiding the collection of undesired, redundant, and expired data, while also addressing the message overhead for the data collection process, and 2) improving the prediction accuracy of indoor thermal comfort, thus helping to make the most adequate decisions. We compared our collection scheme with two other schemes in which we fixed the sensors' sleeping time interval (small and large sleeping time interval). In addition, our ANC learning algorithm is compared with three algorithms: multinomial Logistic Regression Classifier (LRC) [44], Decision Tree Classifier (DTC) [45], and Gaussian Naïve Bayes Classifier (NBC) [46].

We implemented our ANC algorithm using the Keras framework, which provides a set of high-level neural network APIs. Table 4 summarises the main

parameters used to create the prediction model. Thus, we considered the following evaluation metrics:

Table 4: Learning Settings.

Parameters	Values
Dataset collection duration	6 months
Collection time period	July 2017 to December 2017
Percentage of training set	75% of the dataset
Percentage of test set	25% of the dataset
Deep learning Tool	TensorFlow
Weights optimizer	Stochastic Gradient Descent
Activation function	ReLU
Hidden Layers	3 Layers
Number of neurons	6 neurons
Number of epochs	[20-100]
Batch size	20 samples
Learning rate	0.01
Deep learning algorithm	Artificial Neural Classifier (ANC)

- *Time complexity*: This is the generated time complexity required to build the learning model and make some predictions.
- *Accuracy*: This is mainly based on the confusion matrix and measures the percentage of correctly predicted data against the total data. The accuracy was determined by the following formula:

$$Accuracy = \frac{TP + TN}{TN + TP + FN + FP} \quad (1)$$

With TN, TP are, respectively, the true negative and positive, while FN, and FP are false negative and positive, respectively.

- *Recall*: This reflects the percentage of true positives against the total number of false negatives and true positives, as follows:

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

- *Precision*: This represents the percentage of correct positive predictions against the total number of positive predictions, as follows:

$$Precision = \frac{TP}{FP + TP} \quad (3)$$

#### 4.2. Evaluation of Data Collection Scheme

Figure. 7 depicts a comparison between all schemes in terms of the data aggregation ratio, as we increased both the number of rooms (Figure. 7-A) and iterations (Figure. 7-B). We note that our scheme performs better than the other schemes. This is mainly due to the dynamic sensors' sleeping time, which depends on the dissimilarity ratio between each sensor's data.

In addition, we observe that the large-time interval-based scheme generates the lowest data aggregation ratio. Indeed, this scheme sets a large sleeping time interval which causes message overhead in terms of the number of collected data packets, to decrease (Figure. 7-C and D). However, the ratio of gathered useful data was also very low. Moreover, Figure. 7-B shows that a stable ratio of data aggregation was achieved by all schemes. In fact, increasing the number of iterations implies that more data will be sent to the cloud. Thus, the aggregation ratio is greatly affected by the quantity of gathered data, and not by the number of covered rooms. The performance evaluation in terms of the introduced network overhead is shown in 7-(C) and (D). Mostly, the large sleeping time-based scheme and our scheme generate the same overhead, outperforming the small sleeping-time-based scheme. The latter maximises the network overhead because it transfers data more frequently than the other schemes. Although our scheme has the same performance with the large time interval scheme, our scheme enhances the data aggregation ratio which is mainly due to the adaptive and dynamic sleeping interval adopted in our scheme.

#### 4.3. Evaluation of Thermal Comfort Prediction

Table 5 compares the machine learning algorithms (LRC, NBC, DTC, and ANC) in terms of the aforementioned metrics. Our ANC algorithm introduces a high time complexity to build the prediction model and make new predictions. This is mainly due to the neuronal architecture implemented by the ANC algorithm. However, ANC maximises accuracy, precision, and recall evaluation metrics. Although the time complexity of the ANC algorithm is slightly higher than those of the other algorithms, the ANC algorithm

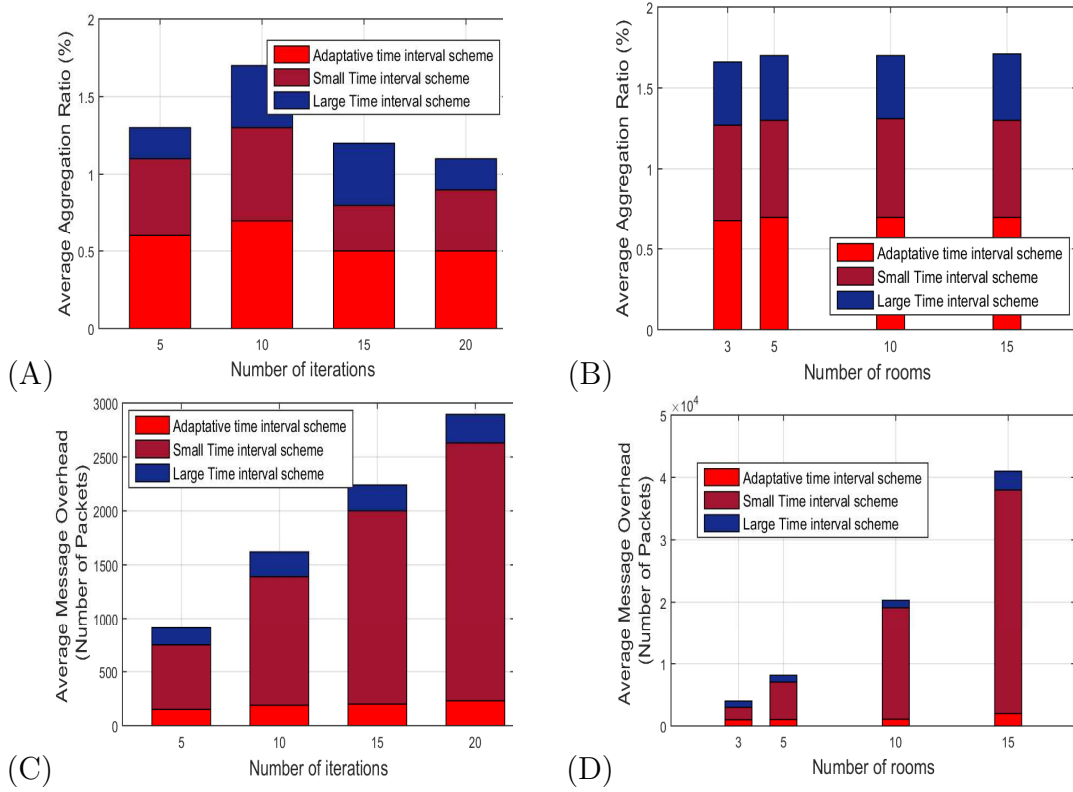


Figure 7: Comparison between our data collection, large, and small sleeping interval based schemes. (A) and (B) The aggregation ratio. (C) and (D) Network Overhead.

clearly improves the prediction accuracy when compared to the other algorithms. This makes ANC more suitable for predicting and monitoring disabled people’s PMV sensations.

Table 5: Performance comparison between learning algorithms.

	LRC	NBC	ANC	DTC
<b>Modeling complexity time</b>	5.51 s	0.16 s	<b>5.54 s</b>	3.03 s
<b>Prediction complexity time</b>	0.04 s	0.19 s	<b>0.21 s</b>	0.04 s
<b>Precision</b>	0.75	0.68	<b>0.98</b>	0.58
<b>Accuracy</b>	0.555	0.49	<b>0.94</b>	0.46
<b>Recall</b>	0.76	0.722	<b>0.97</b>	0.51

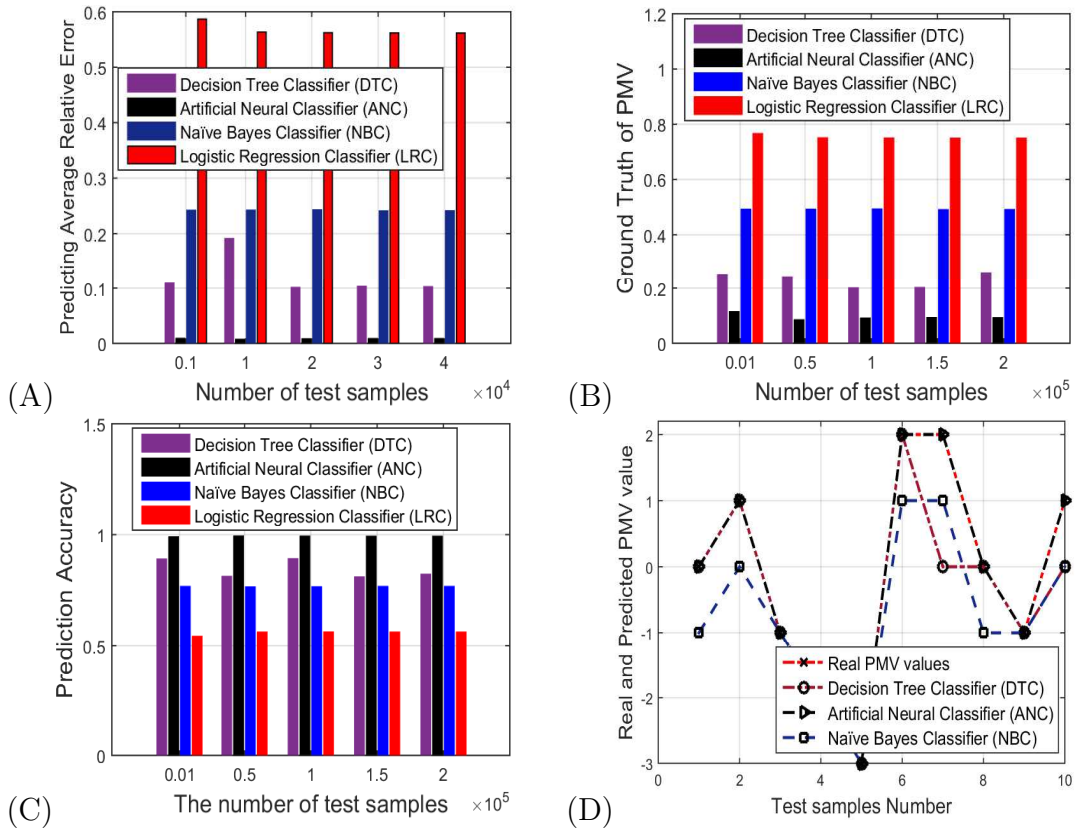


Figure 8: Performance evaluation of machine learning-based schemes.

Figure. 8 presents an evaluation of the prediction models on test subsets,

that is, on data that have never been processed by the created learning models. We observe that the ANC algorithm outperforms all the others in terms of the relative prediction error (Figure. 8-(A)), the predicted ground truth (Figure. 8-(B)), and prediction accuracy (Figure. 8-(C)). In addition, the four algorithms provided stable performance, even when we varied the number of considered test observations. We also note that the LRC algorithm generates the worst performance compared to the other algorithms. Figure. 8-D presents a comparison between the real and predicted PMV sensations corresponding to ten test observations, without including the LRC algorithm. For most of the ten observations, we infer that our ANC algorithm predicts the same PMV values as the real ones, and as compared to the other algorithms. Hence, these results confirm the results obtained in Table 5, illustrating the efficiency of our ANC algorithm and its accuracy in predicting occupants' PMV sensations.

Figure. 9-A evaluates the performance of our ANC learning algorithm in terms of the average predicted PMV values against the real PMV values. These real values were measured through online daily surveys over five weeks. We observe that our ANC algorithm almost succeeds in predicting the same average PMV values, as the real average measured values, except in the first and fifth days. On the first day, our ANC algorithm predicts that the average indoor thermal comfort is cool, while the ten occupants' sensation is cold. Similarly, on the fifth day, our algorithm predicts cool thermal comfort, while the occupants' PMV value is slightly cool. This can be explained by the considerable variation in the response sensations among the ten occupants, especially between slightly cool, cool, and cold sensations, because we considered people with three different disabilities (physical, learning, and neurological). This result is mainly due to disability itself.

Furthermore, to further study the effect of disability on thermal comfort sensations, Figure. 9-B-C-D compare the PMV values predicted using our ANC algorithm, the PMV value for a person without disabilities, and the PMV sensation in three people, each having a physical, learning, or neurological disability. Figure. 9-B clearly illustrates the accuracy of our algorithm in predicting the PMV values for a person with a physical disability. However, we also observed that thermal comfort sensations may vary between people with disabilities and those without disabilities, especially between cold and cool sensations, as well as between hot and warm sensations. Similarly, Figures. 9-C and D show that our ANC algorithm provides an accurate prediction of the PMV value of disabled people, while there are variations in

thermal sensations between the person without a disability and the persons with learning and neurological disabilities. These variations occur mainly between cold and cool; slightly cool and slightly warm; slightly cool and cold; and hot and slightly warm. These results confirm the considerable variations between people with different disabilities, as well as between people with and without disabilities; in the latter case, the variation is mainly due to disability itself. However, our ANC algorithm cannot predict the PMV values for a person without a disability, because our model was initially built considering only data related to people with physical disabilities. Hence, this model is more accurate at predicting the PMV values of such populations.

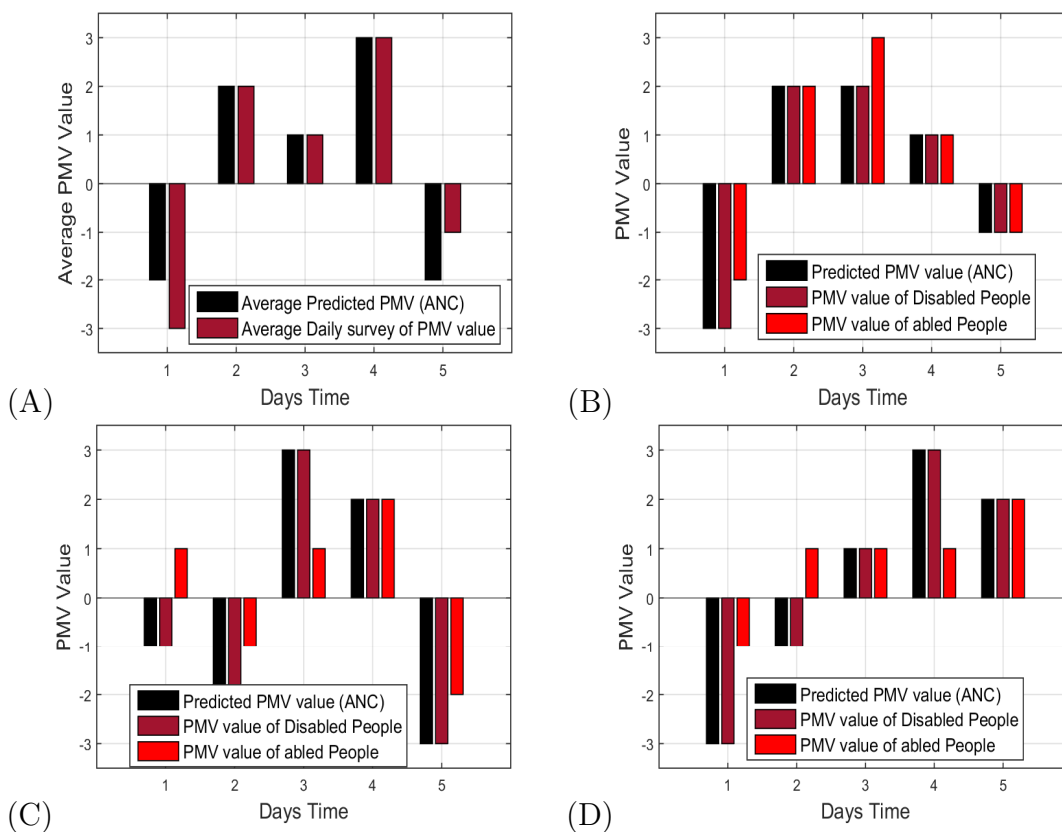


Figure 9: Prediction Evaluation of our Learning Algorithm (ANC), over five days. (A) Average daily survey of PMV value. (B) Physical Disability. (C) Learning Disability. and (D) Neurological Disability.



#### 4.4. Discussion

Based on these results, our schemes outperformed the compared schemes in terms of data collection efficiency and PMV prediction accuracy. We can deduce that our data collection scheme provides an efficient and reliable data collection process by avoiding the collection of non-required data and introducing an acceptable network overhead. In addition, it is obvious that our ANC algorithm exhibits good performance as it significantly improves the model prediction accuracy when compared to the other machine learning algorithms. Moreover, the results of our study confirm that there significant variations in thermal sensations exist between people with and without disabilities, which also confirms the results obtained in[21]. As mentioned before, these specific thermal sensations are mainly due to the disability itself and vary from one disability to another.

Therefore, our deep learning model can be employed not only to predict the thermal comfort of disabled people but also to improve comfort during the four seasons of the year.

## 5. Conclusion

This work investigates the development of a new prediction model for the thermal comfort sensation of people with disabilities. This study is based on the existing thermal PMV sensations and targets three main types of people disability: physical, learning, intellectual, and neurological disabilities. To do so, we first proposed a complete Internet of Things-based architecture that supports the collection of people’s thermal comfort-related data. Thus, we collected real data related to the thermal comfort of ten disabled people over a six-month period. Then, we built a new prediction model for disabled people’s PMV sensations. The study led to the following conclusions:

- Variations exist among the response sensations of disabled people, especially among the PMVs for slightly cool, cool, and cold sensations; this is mainly due to the disability itself.
- There are variations in thermal sensations between people without a disability and people with learning and neurological disabilities. These variations occur mainly between the PMVs for cold and cool; slightly cool and slightly warm; slightly cool and cold; and hot and slightly warm conditions. Therefore, the thermal comfort of disabled people should be considered separately from that of people without disabilities.

- The new prediction model can predict the thermal sensation of disabled people with an accuracy of 94% and precision and recall of 98% and 97%, respectively.
- The developed model can be used to predict indoor thermal comfort in any residential building that houses disabled people. Therefore, our model can help building managers take suitable actions when observing a discomfort situation in a building.

In future work, we will extend our real dataset by considering more people with other disabilities. In addition, we apply deep learning schemes in a distributed manner to ensure the privacy of people’s thermal comfort data.

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